Race and Gender Wage Discrimination and the Business Cycle: a time-series analysis of an estimated Oaxaca-Binder Discrimination Index

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Abstract

A wage-discrimination index is constructed with the Blinder-Oaxaca decomposition method from CPS data across 1980-2018 to examine through time-series analysis whether there is a trend and how cyclical downturns and labor market swings affect the discrimination experienced by three "disadvantaged" groups of workers relative to one privileged group: White Women, Afro-American Women and Afro-American Men versus White Men. A positive deterministic trend in experienced wage discrimination was found for Afro-American Men and a downward trend for White Women. The discrimination experienced by Afro-American Men and Afro-American Women drops respectively by 4.9% and 1.4-4% when there is a downward swing in the economy, while the position of White Women worsens by 1.4-1.8%. Break points in the relationship were found at the beginning of the 2008 Recession and at the end of the following stagnation for two groups. However, the results in the relationship between cycle and discrimination are weakly robust.

*The views stated in this thesis are those of the author and not necessarily those of Erasmus School of Economics or Erasmus University Rotterdam.

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1. Introduction

“Everyone has the right to equal pay for equal work.” With such words reads the 23rd article of the Universal Declaration of Human Rights, yet this fundamental right is hardly respected in our modern society.

A vast amount of literature in labor economics has tried to shed some light on the mechanism behind this social failure that promotes economic inequality, which is discrimination in labor markets. In the paradigm of Discrimination Economics, created by Becker (1956), the wage gap across men and women, or Afro-Americans and Whites, has been explored as a possible determinant for racial and gender disparities in key labor market outcomes.
These outcomes have been found to vary widely across demographic groups and to be highly persistent over time representing an important dimension of income inequality (Cajner, Radler, Ratner, & Vidangos, 2017).

Most of the studies have explored the great divide between Blacks and Whites or Men and Women in the United States, particularly in the evolution of wages or employment in relation to changes in observable characteristics of workers or by the introduction of inclusive policies over time. Discrimination has been investigated mildly in these studies, by considering it the residual from what it cannot be explained. With multiple theoretical attempts in understanding the incentives and disincentives to discriminate from the employer side of the market, the evidence and findings haven’t changed in radial ways over time. In fact, because of the difficulties to observe and measure discrimination very few studies approached empirically this phenomenon in the labor market as something to be explained rather than an explanatory mechanism.

Because of the standard operational practice in the field to use discrimination as the explanan for economic gap across groups, discrimination per se has been left aside in its comportment over time and in its interactions with exogenous factors from the labor market. Hence, the need for an empirical approach that goes beyond the existing theoretical models and a new ramification of the paradigm. That is, what this paper wishes to bring forward.

The novelties that this paper brings to the existing literature are along three different dimensions. First, new CPS-MORG (Current Population Survey) monthly data is analyzed from 1980 up to 2018. Second, the Oaxaca-Binder Wage Decomposition process is used to build three specific wage discrimination indexes for three mutually exclusive minority groups (Afro-American Men, Afro-American Women and White Females). This process is often used in standard labor economics to study labor market outcomes across different groups by decomposing the difference in mean logarithmic wages on regressions in a counterfactual way (Jann, 2008). However, this particular methodology has always been used, to the best of my knowledge, at a cross-sectional level, not as an indexing tool. Third, by having an actual measure of discrimination it is possible to bring wage discrimination at the center of the debate empirically, as the outcome variable, not as the explanatory variable for the wage gap.

These aforementioned conceptual and methodological novelties from which the paper wishes contribute to the ongoing debate will be brought forward by testing three hypotheses in a comparative way.

The first hypothesis concerns the trend of discrimination, constructed from wage differentials, over time. We expect discrimination to exhibit a trend stationary behavior between different groups accordingly to gender or race. Most changes in wage differentials have been explained mainly through skill biased technological change leading to an increase in the productivity of workers and not by major changes in inclusivity by employers over time. Recent studies have also found evidence based on experiments of employers discrimination (Bertrand & Mullainathan, 2004 ;Quilliana, Pagerc, Hexel, & Midtbøen, 2017). Given the persistent nature of discrimination in key market outcomes across groups and the lack of extended research over time the first hypothesis is formalized:

[H1] There is a linear trend of wage discrimination over time.

Deviations from the general trend, if found, will be related to business cycle fluctuations to determine whether the business cycle affects discrimination as the theoretical framework on how discrimination can increase or decrease several suggest (Biddle & Hamermesh (2013), Cajner et al. (2017)). Given that we have no strong prior on the direction of the effect of the business cycle on discrimination we formalize the second hypothesis as:

[H2] There is a relationship between the business cycle and wage-discrimination

To the best of my knowledge, no scholar has empirically investigated this relationship using a continuous index of discrimination. Previous literature uses simple regression analysis on different time frames to quantify whether differences in discrimination exist during booms and recessions.

If the second hypothesis is confirmed, we will run the following sub-hypothesis on the recession following the financial crisis of 2008:

H3) There has been a change in the magnitude of the relationship between the business cycle and wage-discrimination following the financial crisis of 2008.

The hypothesis above will enable us to further explore the topic. In particular, the crisis of 2008 has been acknowledged to have had a profound effect on asset allocation mechanisms through increased regulation in the financial markets and tighter general credit conditions accompanied by unorthodox monetary and fiscal policies. The resulting change in the business environment should make it interesting to examine whether this particular facet of the labor market has been affected.

The paper is organized as follows. In the following section, I will lay down the theoretical framework by reviewing the existing literature in the context of the research. Then, in the data and methodology section I will explain how the index is constructed and introduce the identification strategy. The section is followed by the results from the different tests. Finally, the paper is concluded with the interpretation of the findings and the limitations of the research.

2. Literature Review

In standard economic theory, economists believe that differences in earnings across groups of workers are the reflection of their differences in productivity, with more productive workers out-earning less productive ones. These differences in productivity, are due to the specific characteristics of workers, or better, the human capital that they posses, and they are able to exert.

However, when personal characteristics of workers, which are not related to productivity, such as race, ethnicity, or gender, are valued in the labor market, then we are dealing with discrimination (Arrow, 1971). Discrimination will unfairly widen the difference in earnings across groups and will create barriers for employment (Carneiro, Heckman, & Masterov, 2003).

Following the definition from Kenneth Arrow, it can be said that in a female-discriminating market, men with equal productivity would receive higher wages than women on average.

This phenomenon is a possible determinant for racial and gender disparities in key labor market outcomes, such as for wages and in employment situations. These fundamentally important outcomes vary widely across demographic groups and are highly persistent over time, possibly representing an important dimension of income inequality (Cajner, Radler, Ratner, & Vidangos, 2017). Therefore, the comprehension of the role of discrimination in markets and its determinants is needless to say essential for the creation of a more equitable society (Arrow, 1998).

1. Economics of Discrimination

Discrimination in Economics has a relatively short tradition, being not solely an economic issue, but rather a supplement to sociological and psychological studies.

The Nobel Laurate Gary Becker (1957) was the first economist to deviate from the traditional assumption that firms' behavior in the labor market is solely motivated by profit maximization. He brought forward the alternative notion, that when firms are hiring, they will not always select the most productive people, but rather will give up some profits to express their distaste by hiring on the basis of characteristics that are unequivocally uncorrelated with productivity. That is how discrimination enters the market (Becker, 2013).

If individuals have a taste for discrimination, they will be willing to pay a premium, either directly or indirectly, to express it. This premium will be larger for some individuals that have a "stronger" taste for discrimination, meaning that they will incur a higher cost to discriminate.

2.1 Theories of Discrimination

Following Becker, many economists have been modelling discrimination through diverse frameworks, which can be categorized in two main blocks: the first being made of competitive models that look at individual behavior of agents, and the second of collective models in which groups act collectively against one another.

Competitive models can be further divided into Statistical and Preference based Discrimination. Statistical Discrimination models try to explain the "unequal pay for equal work" by attaching a rational stereotyping behavior to the employers of profit maximizing firms. When these employers have limited information about the productivity of their (possible) employees, they use information about group averages to make fast conclusions about the employees' productivity based on easily observable characteristics; like sex or skin color, and subsequently will discriminate according to the observable characteristics. However, as the firm learns more about the productivity of the employee, the pay of the employee will be more closely linked to the actual productivity rather than the groups' mean average (Altonji & Pierret, 1997) .

Preference based discrimination is simply defined as the dislike or distaste of a group of people. In the model, this type of rationale and behavior is adopted by employers, employees and consumers.

Collective models, on the other hand, emphasize the prejudice, formalized as "taste" by Becker, that some members of the majority group hold against the minority group when interacting with them (Altonji & Blank, 1999) .

Collective models of discrimination are most accredited and adopted outside economic research, in the field of sociology or within legal frameworks. On the other hand, most of the empirical economic literature is based upon competitive models of statistical discrimination.

Important to keep in mind is that there are two specific phenomena to be considered that might bias or affect the discrimination against minority groups. The first being that minority groups are distributed among different occupations compared to White men, who are the privilege group, and the same goes for women, but to a smaller extent. Second, is that within the same occupations there are differences in earnings across groups. The discrimination models and theories previously mentioned in the section can partially explain the second phenomena. On the other hand, the first one is referred to as occupational segregation, which can be partly affected by employment discrimination, and works in complementary to discrimination in widening the economic inequality across groups (Bergmann, 1974).

Some evidence of wage discrimination over the years

Labor market discrimination is difficult to observe and to record. As a result, by no surprise the majority of the empirical work on the matter focusses on the wage/employment gap, and approaches discrimination secondhandedly, as one of the possible determinants of the inequality. In fact, discrimination is commonly seen in economics as the explanans, not as the explenandum.

Therefore, to understand the evolution through the years of the discrimination phenomena, the transformations of productivity and of workers' human capital must be first taken into account first.

Discrimination on the basis of Gender

With the progressive introduction and adaptation of anti-discrimination acts in the United States, the wage gap across men and women has shrunk over time. In particular, the introduction of different reforms, like the 1964 Pregnancy Discrimination Act and the Equal Pay Act of 1963 for women, the former being part of the Fair Labor Standard Act, which prohibits wage discrimination from labor organizations and firms based on gender, has sparked the convergence of wages to the ones of men.

However, the shrinkage of the wage gap exploded only in the late 1970s, when at that time a woman would make 62 cents on the dollar a man made. Gottschalk (1997) found that the period of sharpest decline in the earnings differential for women was during the interval 1973-1994. In 2016 the earnings ratio reached 85 cents per dollar (Blau & Kahn, 2016). Oppenheimer (1976) and Goldin (1990) have shown that the changes in wage gap were mainly due to an increase in education and because of favorable demand shifts for clerical work occupations. Also, the authors show these reductions have occurred in intervals and are not substantially consistent over time. Several other factors, like rising wages and increasing educational attainment have been found to be important in explaining women's increasing labor force participation. The historical development and circulation of market substitutes, household technology for housework and the diffusion of the birth control pill (Bailey, Hershbein, and Miller, 2012) freed women from the housewife condition in which they were previously relegated to with no alternative, (Greenwood, Seshadri, and Yorukoglu, 2005).

However, Blau and Kahn (2006) have shown that the discrimination component has decreased up until the year 1980 but thereafter, discrimination stayed the same. Thus, the wage gap reduction was mainly due to human capital improvement, not change in employer taste. However, according to Carr-

Ruffino (1991), a glass ceiling exists because men at the top are reluctant in promoting women by statistically discriminating them, this accounts for the fact that women are underrepresented in managerial position being only 5% of the total top executives.

Discrimination on the basis of Race

Similar to the economic development that women experienced, discrimination against people of color in the USA had a sharp decline over the period of 1965-1975. The primal factor for this reduction at that time was the political movement for civil rights and the following Civil Rights Act that followed and entered into place in 1964 (Donohue & Heckman (1991),Darity and Mason (1998) and Gottschalk (1997)).

While most studies conclude that although pre-market factors and productive characteristics are important in explaining the white-black wage differential, discrimination is found to be an explanans of about a half or one third of the overall differential (Neal & Johnson, 1995).

A study conducted by Bertrand & Mullainathan (2004), in which the researchers sent fake resumes with randomly assigned Black and White sounding names to job applications, it was observed that the callback rate for resumes with white sounding names, all else equal, that was 50% higher than of those with black sounding names. The experiment was then repeated in New York City after 5 years later, for low-income jobs by Bonikowski et Al. (2010). The results of callback rates were about the same as the previous study, showing that white workers just out of jail have higher chances of being hired than black workers with no criminal record. Along the same line, another field experiment has demonstrated no change over time in the hiring discrimination for US labor markets (Quilliana, Pagerc, Hexel, & Midtbøen, 2017).

Blinder (1973) and Oaxaca (1973) have developed a method that allows to extract a discriminatory component from either the wage gap or the unemployment gap. This type of methodology serves as a substitute to field experiments or in-depth surveying of workers, making it possible to analyze discrimination in a time series. By using the Blinder-Oaxaca method researchers have looked at the difference in discrimination every 10, 20 or 30 years, showing little or no change (Altonji & Blank, 1999).

2.2 Eliminating Discrimination

As D'Amico (1987) notes, the type of research that has been drawn through the years has paid little attention to the actual problem of discrimination, yielding results that have been disappointing because of the studies being erected onto a base that is far too narrow. In order to understand the complex nature of the operating dynamics from which discrimination evolves, the base must be broadened, such that the field can move further from being simply descriptive into becoming etiological in its nature. Hence, the etiological approach in reducing discrimination through the economic framework of cost competition and recessions.

Discrimination and Competition

It ought to be pointed out that, regardless of being a phenomenon as old as humankind, both Arrow (1973) and Becker (1957) have emphasized how discrimination could be eliminated by competition. If firms give up some profits in order to discriminate, then non-discriminating firms will have lower costs which could increase their market share, and this would rule out the discriminating firms. On the other hand, in Becker's concept of a *discrimination coefficient* (1957), from which he derives a wage function at firm-level from the employer's perspective, the premium that the employer pays, expresses his(or her) taste and is not merely a monetary production cost, but it will affect the overall productivity of the firm.

With the advent of free capital markets, capital should end up in the most profitable firms, hence, in this framework, to the non-discriminating ones (Bulow & Summers, 1986). In fact, Cymrot (1985) found evidence that increase in competition in the Major League Baseball reduced or even fully eliminated race discrimination across players. It follows that for firms to be competitive discrimination becomes too costly.

Recession and the cost of discrimination

An alternative mechanism that plays a role in eliminating, or at least in reducing discrimination, is the state of the economy. In a similar manner, a higher degree of competition provides stronger incentives to management and to employers for minimizing their costs (Karuna, 2007), a recession will create incentives to tighten the room of possible costs.

Although very little has been written about the cyclicality of discriminatory wage differentials, there are several mechanisms through which the business cycle could affect discrimination in the labor market (Biddle and Hamermesh, 2013). Two possible mechanisms come to mind, firstly firms leave and enter the market periodically, this process is believed to be influenced by the business cycle (Biddle and Hamermesh, 2013). It remains an open question whether the firms which enter the market in a business cycle boom are more or less discriminatory, the same applies to those that leave during a recession. Secondly, in a recession the increased focus on cost reduction should in theory disincentivize discriminatory behavior by employers if one views discrimination as an additional cost as Becker (1956).

Evidence about cost and incentives in the cycle

Machin & Van Reenen (1993) presented evidence for the pro-cyclical behavior of profit margins for UK manufacturing firms, with firm-level profits falling heavily during the 1980s manufacturing recession. The pro-cyclical view is supported by Lima's and Resende's (2006) findings, however, the authors noted that there are differences on sector and aggregate levels, which cannot be ignored. Additionally, another factor which can account for the relationship between the business cycle and the profit margin is the market structure, with counter-cyclical mark-ups in concentrated industries. It was also found that firms tend to decrease their profit margins during recessions and increase them during times of macroeconomic expansion (Chand and Sen, 2010).

In times of recession, the empirical evidence suggests that retrenchment enhances a firm's recovery from declining performance. Two thirds of small manufacturing firms in the US retrenched during the recession of 1990-1991 (Michael & Robbins, 1998). If the profit margin decreases due to exogenous shocks, then employers' taste for discrimination will become too costly, and discrimination should decrease as well. In a similar manner, if we find ourselves in times of expansion, the profit margin will be greater and the marginal cost of discrimination smaller, yielding a relatively higher rate of discrimination, assuming that the employer is aware of its discriminating costs.

Evidence on business cycle and discrimination

Biddle & Hamermesh (2013) have found evidence showing that the male-female wage gap is counter cyclical in relation to unemployment. The disadvantages faced by women grows when unemployment is higher, the scholars accredit it purely to discrimination, not to composition effects. The wage differential of African-Americans faces pro-cyclical behavior mainly due to observable factors. These factors tend to be more sensitive to fluctuations in the business cycle than the actual discrimination that they experience. In addition, they suggest that the changes in the discriminatory wage differential that are due to the business cycle fluctuations are only for workers that enter or exit the market. There is no effect on the wages of those workers that keep the same employer.

On the other hand, Ashenfelter (1970) claims that cyclical swings in labor market activity over the period 1950-1966 in the US, had virtually no effect on discrimination for all groups. Cajner et al. (2017) examined racial disparities in unemployment over the Business Cycle. The authors found that the unemployment rate for African-Americans is substantially higher and more cyclical than for whites, which is not satisfactorily explained by the difference in observable characteristics between the two groups.

2.3 Great Retrenchment and cost of discrimination

Regardless of being a well explored topic in macroeconomics, the effect of the Financial Crisis of 2007-2008 was hardly ever linked to labor market discrimination. Popov and Rocholl (2018) studied the effect of the Subprime Mortgage crisis on labor market decisions in Germany. They found that there was a significant decline in labor demand, with the employment effect being more pronounced in large firms and wage reduction more pronounced in small firms. Very little evidence was found regarding discrimination, but we know for instance, that the unemployment gap for Afro-Americans and Hispanics has widened dramatically following the Great Recession comparatively to white workers, with disparities remaining substantial according to a study for the US (Cajner, Radler, Ratner, & Vidangos, 2017; Sierminska & Takhtamanova, 2010). Women fared better than men following the 2008 crisis, with unemployment rate by August 2009 being as high as 11% for Men and only 8.3% for women (Hobijn, Şahin, & Song, 2010).

3. Data and Methodology

In order to investigate the second hypothesis a time series regression will be constructed. The relationship between discrimination and business cycle will be measured over the time period 1980-2018 using monthly data. The discrimination index is constructed from the "Current Population Survey Merged Outgoing Rotation Groups". The US Bureau of Labor Statistics queries 50-60,000 households monthly on questions about income and demographic characteristics with industry and geographical longitudinal indicators. The households are interviewed for 4 consecutive months, then ignored for 8 months, and then interviewed for 4 more. One fourth of the households are in outgoing rotation each month. This ensures the representativeness of the population. Official monthly statistics from the U.S. Department of Labor are constructed from this survey data. Most of the relevant literature regarding wage differentials and labor market discrimination made use of CPS data.

The non-self-employed working population has been divided into 4 mutually exclusive groups on the basis of gender and race: Non-Hispanic White Males, Non-Hispanic White Females, Non-Hispanic African-American Males, and Non-Hispanic Afro-American Females. From now on, in the data and methodology section, the group of Non-Hispanic White Males will be referred to as the privileged group and all other groups will be referred to as minority groups.

Business cycle indicators have been retrieved from the Federal Reserve Economic Database, being namely: the NBER Recession Index (USREC) and the change in National Unemployment Rate (∆URATE). The USREC is a dummy variable that takes values of 1 when the American economy is in a recession and 0 if it is in times of expansion, the recession begins on the first day of the period following the peak, and it ends on the last day of the period within a trough. In the last 40 years, ever since January 1980, the US has experienced 5 recessions. The longest and most profound recessions were the one that sparked from the financial crisis, from January 2008 to July 2009, and the one from August 1981 to December 1982. The Unemployment Rate is the number of civilians unemployed over the total labor force. Labor force being restricted to 16 years and older. Evidence has shown the cyclical component of unemployment to follow, and proxy, the business cycle. With sharp rises in unemployment happening in times of recession, and the reductions happening in times of expansion. *Figure A.1* shows the plotted graphs of the two indicators over time.

3.1 Discrimination Index by Oaxaca-Binder two-fold Decomposition

Since there is no available wage discrimination index by month, one can be constructed with the Oaxaca-Blinder decomposition process. The OB has the peculiarity of decomposing the differential of the mean wages for two groups into two components. This is done by using the wage structure of one group as the counterfactual for the other. These differences are then divided into one component that is explained by the differences in characteristics and also an unexplained component. The latter is commonly used as a measure for discrimination in the relevant literature (Weichselbaumer & Winter-Ebmer, 2005), such as unequal pay for equally qualified workers.

The first step is to estimate separate OLS wage functions for each group, namely the privileged group (Non-Hispanic White men) and minority group n (n=2,3,4), that relates to human capital indicators and socio-economic variables to control for observable characteristics across groups. Group 1 will be the baseline group, acting as counterfactual.

The more relevant the characteristics are in the linear regression, the more confidently we can proxy discrimination with the unexplained component.

For month *m* in year *y* we have time *t*, let *w* be the log of the pre-tax weekly earnings and *X* a vector of covariates, β is a vector of coefficients and *u* the error term:

$$\bar{\boldsymbol{w}}_{\mathbf{1},t} = \boldsymbol{\alpha}_{\mathbf{1}} + \bar{\boldsymbol{X}}_{\mathbf{1},t}\boldsymbol{\beta}_{\mathbf{1}} + \boldsymbol{u}_{\mathbf{1},t} \quad \textbf{(1)}$$

$$\bar{\boldsymbol{w}}_{n,t} = \boldsymbol{\alpha}_{n} + \bar{\boldsymbol{X}}_{n,t}\boldsymbol{\beta}_{n} + \boldsymbol{u}_{n,t} \quad \textbf{(2)}$$

Where the variables with a bar above them denote the group mean and α the intercept. The vector of covariates includes age, educational attainment, occupation type, industry type, union membership, average weekly hours worked, marital status and living state. The covariates are all statistically significant at 10% confidence level in the wage structure function. Following, the Oaxaca-Binder, it is computed by decomposing the mean log wage differences into two components:

$$\bar{\boldsymbol{w}}_{\mathbf{1},t} - \bar{\boldsymbol{w}}_{n,t} = \boldsymbol{\beta}_{\mathbf{1}}\left(\bar{\boldsymbol{X}}_{\mathbf{1},t} - \bar{\boldsymbol{X}}_{n,t}\right) + \left[\left(\boldsymbol{\alpha}_{\mathbf{1}} - \boldsymbol{\alpha}_{n}\right) + \bar{\boldsymbol{X}}_{n,t}\left(\boldsymbol{\beta}_{\mathbf{1}} - \boldsymbol{\beta}_{n}\right)\right] \quad \textbf{(3)}$$

The first component of equation (3) shows the differences in log wages accounted for by the differences in averages of the observable characteristics, which represents the “explained” component. The second component, made up of the difference in the intercepts and by the difference in returns to observable characteristics between the two groups, is the ‘unexplained’ part of the differential, which serves as a proxy for discrimination in accordance with

the relevant literature (Blinder (1973), Oaxaca (1973), and (Corcoran & Duncan, 1979)).
For an easier interpretation of discrimination, this shall be a share of the log wage differential:

$$\boldsymbol{DRATIO_{n,t}} = \frac{[(\alpha_1-\alpha_n)+\bar{X}_{n,t}(\beta_1-\beta_n)]}{\bar{w}_{1,t}-\bar{w}_{n,t}} \qquad \textbf{(4)}$$

DRATIO is the percentage of the log earnings differential that is due to discrimination. *Figure A.2* shows the DRATIO over time for the 3 minority groups.

Since the earnings differential over time is determined by the behavior of earnings for the two groups independently, the wage gap can be computed to have an overview of its trend over time for the 3 minority groups:

$$\boldsymbol{WAGEGAP_{n,t}} = \bar{w}_{1,t} - \bar{w}_{n,t} \qquad \textbf{(5)}$$

Some preliminary considerations can be drawn by inspecting the plots of the log-wage-gap and of the discrimination ratio in *Figure 3.1 and Figure A.2*. The wage gap decreased over time for any group of women, with white women having experienced the most substantial reduction in the log-wage-gap.

White women have the highest average discrimination rate relative to White men in comparison to the other two groups, it accounts for 54.75% of the log wage differential with a standard deviation that however is the smallest one being about 4.49%. On the other hand, Afro-American men have the smallest average discrimination rate and the largest standard deviation, the former being 32.14% and the latter 10.87%. The descriptive characteristics of the wage discrimination rate for Afro-American women lays in between the other two groups, with a mean of 42.49% and a standard deviation of 5.93%.

Table 3.1 Descriptive Statistics

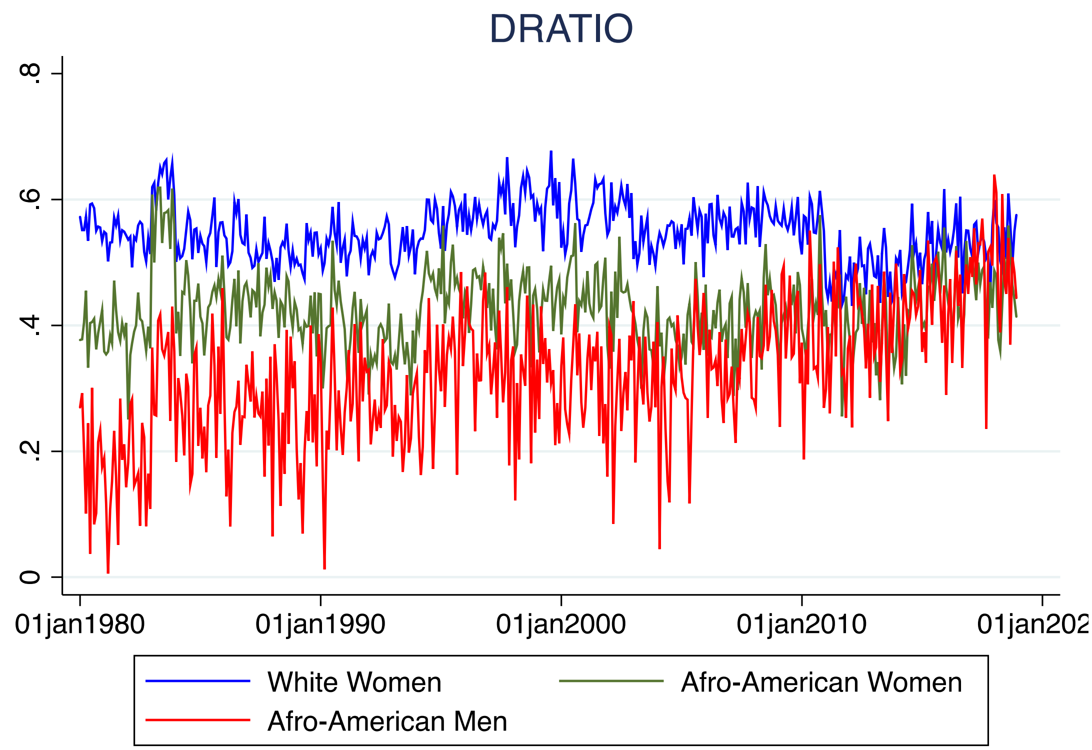
		$DRATIO_{n,t}$	
	White Women	**Afro-American Women**	**Afro-American Men**
mean	.547	.425	.321
St. deviation	.045	.059	.109
minimum	.431	.250	.005
maximum	.678	.619	.639
		$WAGEGAP_{n,t}$	
	White Women	**Afro-American Women**	**Afro-American Men**
mean	.446	.483	.294
St. deviation	.080	.058	.040
minimum	.289	.349	.179
maximum	.639	.667	.421

Note: there are 468 observations per variable

The average wage gap of White Women is about 0.446 with a maximum level of 0.639 and a minimum of 0.289. Afro-American women have experienced and still do the highest difference in wages compared to white men, in terms of maximum and average levels, these respectively being 0.667 and 0.483. Afro-American Men have a mean wage gap of 0.294 with a minimum of 0.179 and a maximum of 0.421.

From the descriptive statistics it appears that gender is a stronger determinant for inequality, both in term of wages and of discrimination, than race. For the group that has both characteristics, Afro-American Women, their wage and discriminatory situation lays in between the one of the other two groups, so seemingly being that race and gender do not add up in terms of discrimination, but rather even out one another.

Figure 3.1 Discrimination rate over time



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3.2 Deterministic trend regression

In order to test the first hypothesis, the methodological approach will be to construct a simple regression of the discrimination ratio against its deterministic trend. The equation of the model is the following:

$$\boldsymbol{DRATIO_{n,t}} = \alpha_n + \lambda_n\, \boldsymbol{trend_t} + \boldsymbol{v_{n,t}} \quad \textbf{(6)}$$

v_t is the stationary disturbance over time, λ captures the deterministic trend of the time series and α is the intercept. If the trend coefficient is statistically significant, the first hypothesis cannot be rejected.

3.3 Static Approach: Multivariate Linear Regression

To understand the relationship of the business cycle with discrimination, two Multivariate linear regression will be run, one with NBER Recession Indicator as variable of interest (USREC), and the other one with the change in unemployment rate (∆URATE). Being the USREC a binary variable its interpretation as a business cycle indicator is limited, however the change in unemployment rate can tell us more about the behavior of discrimination beyond the times of recession. Hence, the need of the two models. The model equations are the same across all three minority groups (White Women, Afro-American Women and Afro-American Men) and are the following:

$$\boldsymbol{DRATIO_{n,t} = \beta_{0,n} + \beta_{n,1}USREC_{t} + \beta_{n,2}trend_{t}} + \varepsilon_{n,t} \tag{7}$$

$$\boldsymbol{DRATIO_{n,t} = \beta_{n,0} + \beta_{n,1}\Delta URATE_{t} + \beta_{n,2}trend_{t}} + \varepsilon_{n,t} \tag{8}$$

With β_0 being the intercept, $\beta_1$the coefficient of the variable of interest, β_2 the coefficient for the control variable of the wage gap and ε_t the error term of the residuals. However, regression without control for the deterministic trend will be run as well for both models in order to assess the change in the predictors before and after controlling.

3.4 Dynamic Approach: Autoregressive Distributed Lag Model (ARDL)

To capture the cyclical essence of the relationship, the two previous linear regression models have been augmented by inserting statistically significant lags, in such way, the equations are transformed into Autoregressive Distributed Lag Models. The models were estimated following the standard two steps for ARDL according to Stock and Watson (2012). First the order of the AR model was estimated using a correlogram of the dependent variable (FigureA4). Subsequently, lags were added for the recession indicator in model

1 and the unemployment rate for model 2. A control for trend is inserted following the static model building from section 3.3. Several models were compared using the Schwarz criterion and log likelihood which also resulted in a drop of the insignificant parameters for estimator variance minimization purposes. The resulting Autoregressive Distributed Lag models for the three group are specified as follows:

$$\boldsymbol{DRATIO_{n,t}} = \beta_{n,0} + \beta_{n,1}\boldsymbol{DRATIO_{t-1}} + \beta_{n,2}\boldsymbol{DRATIO_{t-2}} + \delta_{n,1}\boldsymbol{USREC_{t-1}} + \delta_{n,2}\boldsymbol{USREC_{t-2}} + \boldsymbol{\varphi_{n,t}trend_{t}} + \varepsilon_{n,t} \quad \textbf{(9)}$$

$$\boldsymbol{DRATIO_{n,t}} = \beta_{n,0} + \beta_{n,1}\boldsymbol{DRATIO_{t-1}} + \beta_{n,2}\boldsymbol{DRATIO_{t-2}} + \delta_{n,1}\Delta\boldsymbol{URATE_{t-1}} + \delta_{n,2}\Delta\boldsymbol{URATE_{t-2}} + \boldsymbol{\varphi_{n,t}trend_{t}} + \varepsilon_{n,t} \quad \textbf{(10)}$$

If the model coefficients for the variable of interest are statistically significant, we will not be able to reject the second hypothesis.

3.5 Quandt-Andrews break test

The ARDL model assumes that the relationship between the variables are constant over time, however there might be exogenous factors that cause changes in the underlaying relationship, particularly during the Great Recession following the Financial Crisis of 2008. Because of the uncertainty about in what specific month of the recession a change in the relationship might have occurred, the Quandt Andrews break test is chosen for its capability of testing for break points in every month of the data set. If the break point is found in the time span between March 2008 to June 2009 we cannot confidently reject the third hypothesis. This particular interval is chosen based on the official announcements of the American Labor Department about the beginning and end of the recession. However, the interval can be stretched up to June 2011 if we base include the times of stagnation that followed the recession.

4. Results

Although we believe that there is a causal relationship between the business cycle and discrimination, we will not seek causation because of the rarity of the exogeneity assumption to hold in an economic study. Nonetheless, some interesting relations can be drawn from our empirical exercise.

4.1 Deterministic Trend Results

The results from the Deterministic Trend Model per group are summarized in Table 4.1. In the first column from the left we have the trend model of our Discrimination Ratio for White Women. The central column shows the results for Afro-American Women and the right most column displays the coefficients and parameters for the group of Afro-American Men. The trend direction, the magnitude of the coefficient and significance vary widely across the three groups. The Discrimination for White women has a negative deterministic trend that it is statistically significant at the 1% level, but it has virtually no monthly magnitude, that equal to 4.2x10^-5. If discrimination would decrease to zero from its initial endowment of 55.7%. it would take approximately 1085 years. The R2 is about 1.6% and the F-statistic is high enough for the overall model to be jointly significant at the 1% level. However, by inspecting *Figure A.3a* we can observe that the fitted deterministic line does not fit the data points well.

The model for Afro-American women cannot be interpreted because we find no deterministic trend. The F statistic of the regression is 0.03, which is highly insignificant and its R-squared equals 0.01%. The trend that follows is statistically insignificant with no magnitude. Similar to the deterministic trend for white women, by inspecting *FigureA3.b* we can observe the strong and apparent random spikes in both directions, which cannot be captured by a linear relationship.

On the other hand, the trend model for Afro-American Men has a relatively strong explanatory power with an R squared of 37.85% and a F-statistic of 269.93. The trend coefficient is positive and statistically significant at the 1% level. The trend shows a 0.1 % increase in discrimination per month.

Table 4.1 Results for Deterministic Trend Models

	$DRATIO_t$		
(6)	**White Women**	**Afro-American Women**	**Afro-American Men**
constant	0.557***	.426***	.205***
	(.004)	(.006)	(.008)
time	-0.000***	-0.000	.001***
	(.000)	(.000)	(.000)
Adjusted R2	0.016	0.0001	0.3785
# of observations	468	468	468
F-statistic	8.28***	0.03	269.93***

Note: * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01 and robust standard errors are in parenthesis

The α represents the initial level of discrimination in January 1980, this is statistically significant at the 1% level for all 3 groups, with White Women experiencing the highest rate of Wage Discrimination, this amount equaling 55.7% of the wage gap, followed by Afro-American Women, with 42.6% and finally Afro-American Men with a level of discrimination of 20.5%.

There appears to be a convergence in the level of discrimination experienced at least by two groups, the groups for White Women and for Afro American Men. While White Women are experiencing a very tiny reduction over time from the initial very high level of discrimination, Afro-American Men are experiencing a much steeper increase of 0.1% monthly which will bring them closer to White Women than to their initial level of 20%. We cannot say much for Afro-American Women, just that their discrimination rate lays in between the other two groups in January 1980.

4.2 Results from the Static Models

The results vary across different dimensions in the models. Table 4.2 summarizes the findings from 12 regressions. The explanatory variables of

Model 1 from equation 7 are jointly significant at the 1% level for Afro-American Men and White Women. They yield an explanatory power of 2.6% for White Women and of 38.1% for Afro-American Men as measured by the R squared. Moreover, the effect of the control variable, our time trend, is significant at least at the 1% level for both Afro-American Men and White Women. The R-squared for Afro-American Women is of 0.7%. Contrary, the F-statistic shows that the model built for this particular group has no predictive capability. This is in line with our previous findings of no deterministic trend for Afro-American Women; hence we should analyze the results from the model with no trend control. The R-squared in in question is of 0.6% and the model is significant at least at a 10% level.

It is important to point out how for Afro-American Men, both in Model 1 and in Model 2, when the trend control is inserted, the F-statistic increases sharply. With this rapid increase, the business cycle indicator loses magnitude and becomes insignificant, showing how the relationship was biased and the deterministic trend accounts for most of the changes in the Discrimination Ratio.

Our variable of interest for model 1, *USREC,* is statistically significant at least at the 10% without control and at least at 5% when controlling for White Women and at least at the 5% level for Afro-American Women. Interestingly enough it shows a positive coefficient for White Women and negative coefficient for Afro American Men and Women.

This indicates that when the economy is in a recession, White Women experience 1.4% more discrimination than in times of expansion. On the contrary, the discrimination experienced by Afro American women is reduced by 1.4% in times of recession.

Table 4.2 Results of the static model

	$DRATIO_t$					
	White Women		**Afro-American Women**		**Afro-American Men**	
Model 1 (7)						
constant	.546***	.555***	.427***	.429***	.327***	.209***
	(.002)	(.004)	(.003)	(.006)	(.005)	(.009)
$USREC_t$	.016***	.014**	-.014**	-.015**	-.050***	-.018
	(.005)	(.006)	(.007)	(.008)	(.015)	(.011)
$trend_t$		-.000**		-.000		.001***
		(.000)		(.000)		(.000)
Adjusted R2	0.002	0.026	0.006	0.007	0.023	0.381
F-statistic	9.43***	7.19***	3.85*	1.94	10.60***	139.29***
Model 2 (8)						
constant	.548***	.557***	.425***	.426***	.321***	.206***
	(.002)	(.004)	(.003)	(.006)	(.005)	(.008)
$\Delta URATE_t$	.016	-.013	-.040**	-.041**	-.056*	-.034
	(.013)	(.013)	(.017)	(.017)	(.029)	(.023)
$trend_t$		-.000***		.000		.000***
		(.000)		(.000)		(.000)
Adjusted R2	0.004	0.019	0.132	0.014	0.008	0.248
F-statistic	1.50	5.31***	5.58**	2.8*	3.64*	137.43***

Note: number of observation is of 468 per model. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01 and robust standard errors are in parenthesis.

The variables in Model 2, the regression with change in unemployment rate as independent variable, are jointly statistically significant at least at the 1% level for the regressions of Afro-American Men and White Women with control. These models have a smaller F statistic and smaller adjusted R squared than Model 1. Afro-American Women have a higher R-squared and F-statistic with joint significance of the variables of at least at the 5% level without control variable and 10% with trend control compared to Model 1. We can observe how the sign of the coefficient for the variable of interest is now the same for all three categories of workers. The coefficients of the change in unemployment rate are statistically significant at the 10% level for Afro-American Men without trend control and at least at the 5% level for Afro-American Women. The coeffcients show a negative association with the Discrimination Ratio. For Afro-American Women a positive change of 1% in the civilian unemployment rate is associated with a reduction of wage discrimination by 4% For Afro-American Men it is 5.6% without accounting for trend and 3.4% with trend. White Women might experience a reduction of 1.3% in discrimination. However, it is important to keep in mind that this association is insignificant for Afro-American Men when the control variable is present and it is insignificant for White Women regardless of the control variable.

4.3 Results from the Dynamic Models

The results of ARDL models 1 and 2 are in line with the results from static models 1 and 2. However, the plausibility of the model as measured by the log likelihood of the ARDL per group, has an opposite order of which group has the best fitted model compared to the static models. White Women having the highest log likelihood, Afro-American Men the lowest and Afro-American Women are in between. For Model 1, the dynamic model for White Women has insignificant coefficients for the control variable and for the first lag on the USREC. However, the presence of these variables maximizes the log likelihood of the model. The second lag of the variable of interest is statistically significant at least at a 10% significance level and has a magnitude of 1.8%. It can be translated into a follow up increase of discrimination two months after the economy was in recession.

Regarding Afro-American Women, the first lag of the *USREC* is significant at least at a 10% level and it has a negative magnitude of 2.4% without trend control and 2.5% with trend control. The control is insignificant and so is the first lag of the USREC regardless of the presence of the control.

Table 4.3 Results of the dynamic model

	$DRATIO_t$					
	White Women		**Afro-American Women**		**Afro-American Men**	
Model 1(9)						
β_0	.548***	.557***	.427***	.431***	.327***	.208
	(.005)	(.012)	(.006)	(.012)	(.012)	(.011)
$DRATIO_{t-1}$	.419***	.412***	.387***	.387***	.339***	.148***
	(.045)	(.046)	(.050)	(.050)	(.045)	(.048)
$DRATIO_{t-2}$	.279***	.277***	.183***	.183***	.282***	.097**
	(.042)	(.042)	(.046)	(.047)	(.045)	(.048)
$USREC_{t-1}$	-.016	-.018	-.024*	-.025*	-.024	-.024
	(.013)	(.013)	(.014)	(.014)	(.027)	(.027)
$USREC_{t-2}$	.018*	.018*	.008	.007	-.003	.004
	(.011)	(.011)	(.014)	(.014)	(.028)	(.027)
$trend_t$		-.000		-.000		.001***
		(.000)		(.000)		(.000)
Loglikelihood	900.7486	901.295	724.9602	725.0187	456.1488	494.0728
Wald chi2(5)	296.87***	278.05***	181.49***	179.53***	180.01***	188.08***
Model 2 (10)						
β_0	.547***	.557***	.051***	.427***	.321***	.205**
	(.005)	(.012)	.002	(.014)	(.012)	(.010)
$DRATIO_{t-1}$	.408***	.406***	.384***	.384***	.347***	.152***
	(.045)	(.046)	(.049)	(.049)	(.045)	(.048)
$DRATIO_{t-2}$	.288***	.285***	.180***	.180***	.281	.088*
	(.042)	(.043)	(.046)	(.047)	(.045)	(.047)
$\Delta URATE_{t-1}$	.002	.002	-.015	-.015	-.018	-.018
	(.009)	(.009)	(.015)	(.015)	(.027)	(.025)
$\Delta URATE_{t-2}$	.015	-.014	-.019	-.020	-.044*	-.049**
	(.009)	(.010)	(.014)	(.014)	(.025)	(.023)
$trend_t$		-.000		.000		.000***
		(.000)		(.000)		(.000)
Loglikelihood	900.3536	900.8542	724.8685	724.8935	456.2666	495.5474
Wald chi2(5)	289.14***	271.37***	176.65***	175.43***	185.95***	193.13***

Note: * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01 and robust standard errors are in parenthesis. Columns 1,3,5 are without control variable, columns 2,4,6 are with control

The USREC is insignificant for Afro-American Men in both its first and second lag. The trend is significant at least at the 1% level and it has a magnitude of 0.1%. The *USREC* has a negative value of 2.4% in the first lag and changes both in sign and magnitude in the second one.

The second model is overall a worse fit than the first one for White Women and Afro-American Women, given higher log-likelihood values for all three groups and WILD CHI SQUARED. However, it is better for Afro-American Men in those dimensions. In fact, the variable of interest is statistically significant at least at the 10% level without control and at least at the 5% one with the trend for this group. The relationship is negative with a magnitude of 4.4% without trend and 4.9% with its presence. The trend control is significant at a 1% level for the group. The ∆URATE at lag 1 is smaller than in the second lag, showing the relationship possibly being delayed across all groups. White-Women and Afro-American Women have no significant coefficient for any regarding the lags of the change in unemployment rate or the control variable.

4.4 Results from the Quandt-Andrews test

Three different break points were found for the three different groups. The Quandt-Andrews tests were run only on the regressions with the unemployment rate, not on the ∆USREC, as the test cannot be run on binary variables. The break point found for White Women was in January 2011, for Afro-American Women on April 1988 and for Afro American Men on March 2008.

5. Discussion and Conclusion

This paper attempts to empirically estimate a discrimination index from the wage gap and to analyze its trend and cycle, by testing its relationship with the business cycle. Multiple regressions and time series analysis were used, showing that both static and dynamic changes in the state of the economy can be linked to changes in average discrimination experienced by three different demographic groups of workers in the United States.

The presence of statistically significant deterministic trends in the Average Discrimination Rate experienced, from the index built on the two separate groups of White Women and of Afro American Men, gives us reason to believe that we cannot reject the first hypothesis, and that discrimination is persistently increasing for Afro-American Men and somewhat decreasing for White Women over time. However, the first hypothesis for the group of Afro-American Women, given that a deterministic trend was not found, could be rejected. Nevertheless, as a robustness check, Dickey Fuller tests with trend from zero up to two lags in the variable *DRATIO* were run, providing results that reject at a 1% significance level the presence of a Unit Root in favor of trended stationarity for all three groups, Afro-American Women included. Hence, we can derive that the evolution over time for our dependent variable is not due to a random walk for any group of workers.

The opposite direction of the statistically significant trends for the two groups captures the distinctive disadvantage that each group has experienced in the past 40 years. Changes in the perception of employers based on the productivity of these two groups or on their "likeliness" may explain their development over time. Noticeably to point out is that there appears to be a convergence towards a possible structural rate of discrimination in the wage gap. We can only speculate on the reasons behind this mechanism, but we would suppose that there will always be a share of employers that will discriminate regardless of the transformations that might occur in the public sphere.

The results from the models built to test our second hypothesis of relationship between business cycle and discrimination vary widely across different dimensions. These differences shed light on the weak robustness in our 24constructed models. However, when we inspect the results from the models with preferred specifications, a relationship between the two economic phenomena appears to be present.

21 out of the 24 models used to capture the relationship between the business cycle and discrimination yielded similar results, showing a negative relationship between the two phenomena. However, only 9 of these 21 models have statistically significant coefficient for the variable of interest, and only 5 of these have all variables jointly significant at least at a 5% level. The weak robustness of the models is evident, but some models are preferably specified because of the idiosyncratic nature of discrimination experienced by each group, which is reflected upon the indices built.

The four models, with the recession indicator for discrimination experienced by the group of White Women, have a better fit and joint significance of the variables than the four models with the change in unemployment rate. The former four, both statically and dynamically provide a significant relationship at least a 10% level with a magnitude between 1.4-1.8%. These coefficients for the group are of positive sign. It implies a greater experienced disadvantage in times of recession. This is a different outcome given the opposite sign of the relationship compared to the other two groups. However, when the wage discrimination for the group of White Women is modelled against the change in unemployment rate, the continuous proxy for the business cycle, the sign of the relationship changes across lags and across presence of the control variable, yielding no significance. Following the limited evidence provided we could argue that negative demand shocks increases the discrimination experienced by White Women. Yet, these statistical differences are not very large, so it is difficult to define what the direction of the relationship is. Anyhow, the relationship between the binary measure of cycle and the average wage discrimination exists, therefore we fail to reject the second hypothesis for this group of workers.

The models that use the change in unemployment rate have a lower fit than the ones with the recession indicator, with lower statistical significance in the coefficient of the relationship for all groups apart from Afro-American Men. This specific group with this particular measure of business cycle meets the requirement in terms of preferred specifications. The presence of trend control isolates much of the effect of the cycle, providing an inverse relationship in the magnitude of 4.9% with changes in unemployment rate. Consistently with prior literature on how racial disparities decrease with rise in unemployment (Biddle & Hamermesh, 2013) we fail to reject the null.

For the group of workers of Afro-American Women, the relationship between average wage discrimination experienced and the business cycle is consistent across the dynamic and the static models in the direction of the relation. Notwithstanding, it varies in magnitude across the variables of interest. With an increase of 1% in the unemployment rate, discrimination drops by 4% in the same month and of 1.5% in the following month. In the onset of a recession the average discrimination rate experienced by this particular group of workers drops about 1.4 to 2.4%. Hence, we fail to reject the second hypothesis for the group of Afro-American Women as well.

We failed to reject H2, implying that there is a relationship between business cycle and wage discrimination, we have reasons to believe that this relationship is negative given the evidence found, with afro American Men benefitting the most from downward swings in the economy.

For the skeptic reader the overall methodology was adopted to test the relationship of the business cycle with the wage gap, which can be found in appedices A.1, A.2 and A.3. Given that the wage gap is a well-established measure of differences across groups and it has been examined widely throughout the history of Discrimination Economics, it seems necessary to compare the findings of the estimated *DRATIO* with the Wage-gap. Conversely, the wage gap can be explained by many observable factors, both from the dimension of the workers' human capital and from exogenous factors, as from minimum wage policies or inclusive policies. However, the results show virtually no relationship across wage gap and business cycle in terms of significance. This is in line with Ashenfelter (1970). Consequently, this provides evidence of the need of analyzing discrimination by the use of a different metric from the wage gap, which has intrinsic characteristics that are mostly attributed to occupational segregation, not to discrimination *per se*.

For what it concerns our third hypothesis of change in relationship, the only group which can be examined in this framework is Afro-American Men, because the relationship found with the change in unemployment rate is very robust for this group. A break date in the standing relationship was found in March 2008, at the very beginning of the recession. We fail to reject the third hypothesis for this group of workers.

There may be important limitations residing in the dataset used. The CPS-Morg data is built on household surveys. The outreach in the population might have changed over time. One would presume that in the 80s it was harder to reach the poorest people and the ones who were more discriminated, whether in the last 10 years the CPS might have been undertaken by selection of the American population that it appeared to be invisible in the past. If this were to be true, it would undermine the creation of the index. However, if one presumes that this outreaching phenomenon happened proportionally across all groups, White Men included, then the selection bias is absent.

A second limitation may reside in the Oaxaca Blinder decomposition method. The discrimination coefficient is the residual, which represents all the unobservable variables not included and not explained, hence the fear of omitted variable bias. However, if we assume that the changes in omitted variables are consistent across groups and over time, then we can comfortably bypass the bias. However, we have to admit that this assumption is unlikely.

Given the limitations and findings, we will now move over the normative aspect of the paper, with recommendations for further research and policy implications. The study was conducted for three groups in the United States, the findings lack external validity given the unique nature of the labor life that each minority group has. Hence, studies in different countries for smaller minorities seem to be relevant to let the paradigm be expanded.
More observable characteristics should be included in the Oaxaca-Binder wage structure, even a non-linear wage structure might be of great use to model and measure wage discrimination. Segmentation of the groups across cities and

industries, with industry and regional specific demand shocks might yield a closer and more accurate estimation of the nature of the relationship between the business cycle and wage discrimination.

Many authors, even Becker (1953), have advocated how important competition is in the fight against discrimination. However only one minor study was done for the MLB (Cymrot, 1985). Therefore, with the now existing standpoints to measure discrimination, it seems pressing to study the effects and interactions of the degree of competition within industries and areas with discrimination.

The policy implications from the findings should be of relevance to policy makers who believe in the 23rd article of the Human Rights declaration. The countercyclical nature of the relationship makes it possible to tax or penalize employers economically in times of expansions, without undermining their competitiveness. Consequently, by funding the governmental budget and fighting the economic injustice.

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Appendix

Tables

Table A.1 Results from deterministic trend of the wage gap

	$WAGEGAP_t$		
(6)	**White Women**	**Afro-American Women**	**Afro-American Men**
constant	0.580***	.551***	.281
	(.002)	(.004)	(.004)
time	-0.001***	-.000***	-.000***
	(.000)	(000)	(000)
Adjusted R2	0.922	0.451	0.036
# of observations	468	468	468
F-statistic	5158.52***	337.07***	17.55***

Note: * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01 and robust standard errors are in parenthesis. Columns 1,3,5 are without control variable, columns 2,4,6 are with control

Table A.2 Results from static model of the wage gap

	$WAGEGAP_t$					
	White Women		**Afro-American Women**		**Afro-American Men**	
Model 1 (7)						
constant	.440***	.577***	.479***	.549***	.295***	.281***
	(.004)	(.002)	(.003)	(.004)	(.002)	(.004)
$USREC_t$	.051***	.013***	.029***	.009	-.004	-.000
	(.013)	(.003)	(.010)	(.006)	(.006)	(.005)
$trend_t$		-.001**		-.000***		.000***
		(.000)		(.000)		(.000)
Adjusted R2	0.043	0.9254	0.0256	0.4537	0.001	0.036
F-statistic	16.17***	2766.38***	8.18***	173.06***	0.50	8.76***
Model 2 (8)						
constant	.446***	.579***	.483***	.551***	.294***	.281***
	(.004)	(.002)	(.003)	(.004)	(.002)	(.004)
$\Delta URATE_t$	.036	.010*	.009	-.0046	.002	.005
	(.025)	(.006)	(.019)	(.012)	(.012)	(.012)
$trend_t$		-.000***		.000		.000***
		(.000)		(.000)		(.000)
Adjusted R2	0.006	0.923	0.001	0.451	0.000	0.037
F-statistic	2.06	2604.48***	0.22	169.65***	0.03	9.00***

Note: * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01 and robust standard errors are in parenthesis. Columns 1,3,5 are without control variable, columns 2,4,6 are with control

Table A.3 Results from dynamic model of the wage gap

	$WAGEGAP_t$					
	White Women		**Afro-American Women**		**Afro-American Men**	
Model 1	**(9)**			**(10)**		**(10)**
β_0	.448***	.557***	.480***	.549***	.294***	.281***
	(.041)	(.004)	(.008)	(.007)	(.002)	(.005)
$WAGEGAP_{t-1}$	.489***	.277***	.396***	.239***	.179***	.157***
	(.040)	(.045)	(.045)	(.047)	(.046)	(.046)
$WAGEGAP_{t-2}$	.493***	.282***	.346***	.193***	.078*	.057
	(.039)	(.042)	(.045)	(.046)	(.046)	(.047)
$USREC_{t-1}$	.007	.009	.026**	.021*	.012	.014
	(.010)	(.009)	(.013)	(.011)	(.017)	(.018)
$USREC_{t-2}$	.003	.004	-.008	-.013	-.017	-.016
	(.008)	(.008)	(.013)	(.012)	(.016)	(.018)
$trend_t$		-.000		-.000***		.000***
		(.000)		(.000)		(.000)
Log likelihood	900.7486	1178.446	802.5997	831.9303	848.5887	853.4497
Wald chi2(5)	8461.9***	1624.1***	340.9***	192.2***	19.75***	23.82***
Model 2 (11)						
β_0	.451***	.580***	.482***	.551***	.294***	.281**
	(.042)	(.004)	.008	(.007)	(.003)	(.005)
$WAGEGAP_{t-1}$	.488***	.288***	.401***	.241***	.184***	.161***
	(.040)	(.046)	(.044)	(.047)	(.046)	(.046)
$WAGEGAP_{t-2}$	.495***	.295***	.348***	.191***	.080*	.059
	(.039)	(.043)	(.045)	(.046)	(.048)	(.048)
$\Delta URATE_{t-1}$	.005	.006	-.000	-.003	-.006	-.004
	(.005)	(.006)	(.013)	(.013)	(.011)	(.011)
$\Delta URATE_{t-2}$	-.002	.000	-.005	-.009	-.014	-.012
	(.006)	(.000)	(.012)	(.012)	(.010)	(.010)
$trend_t$		-.000***		-.000***		.000***
		(.000)		(.000)		(.000)
Log likelihood	1140.536	1176.023	801.084	830.947	848.561	853.297
Wald chi2(5)	8914.8***	1524.3***	352.4***	195.8***	21.86***	25.11***

Figures

Figure A.1 Business Cycle Indices over time

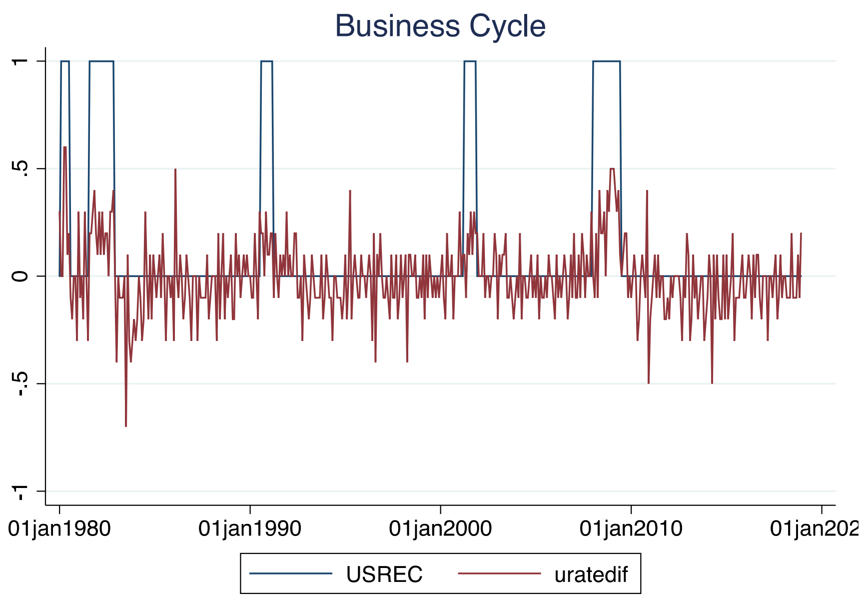

Figure A.2 wage gap over time

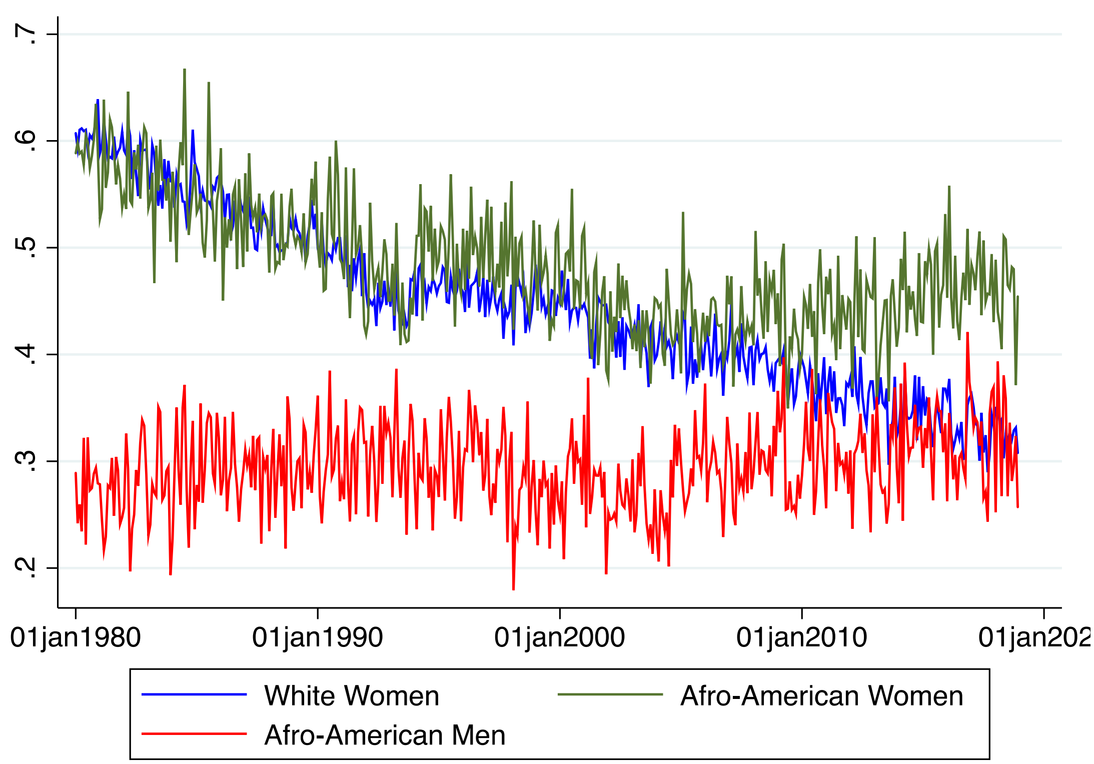

Figure A.3a Discrimination trend for White Women

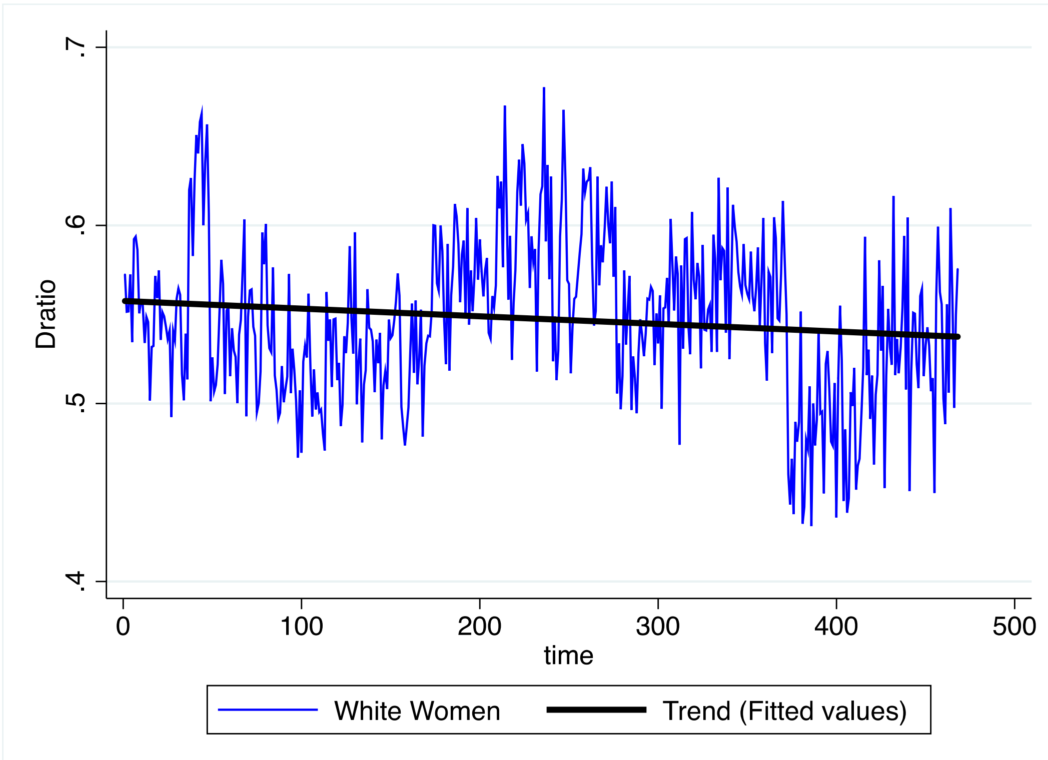

Figure A.3b Discrimination trend for Afro-American Women

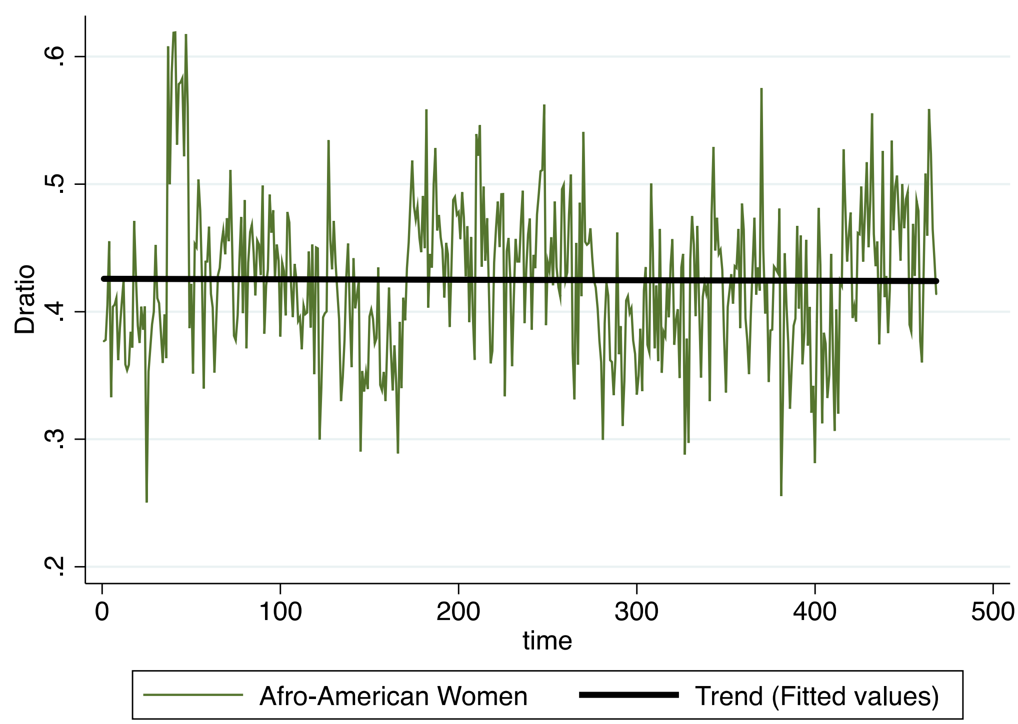

Figure A.3c Discrimination trend for Afro-American Men

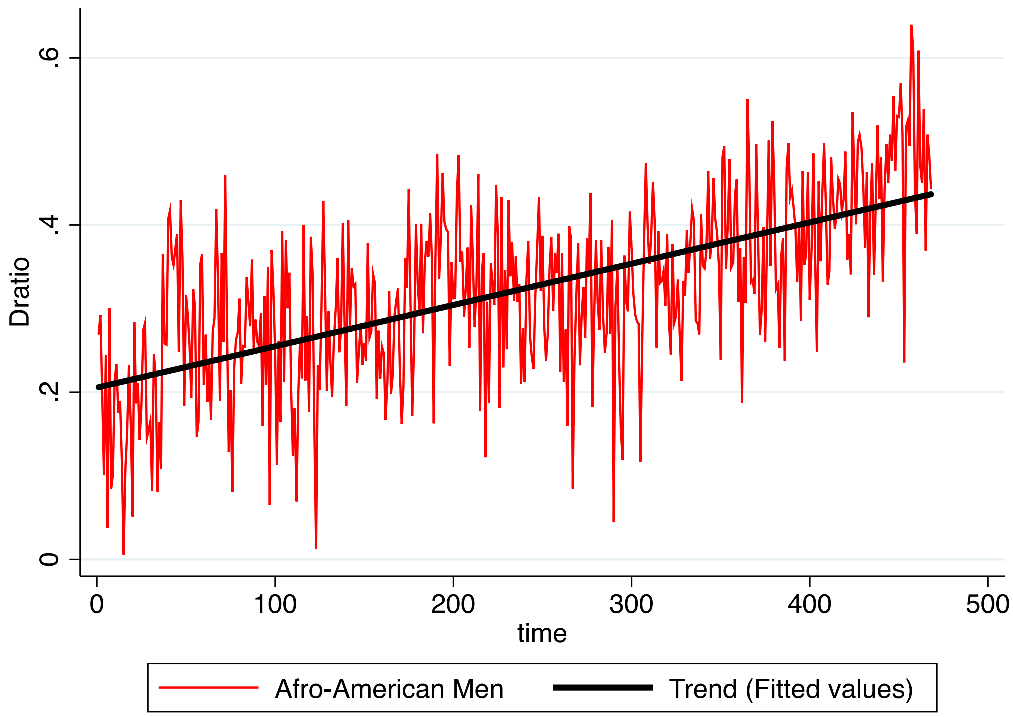

Figure A.4 Autocorrelogram for White Women

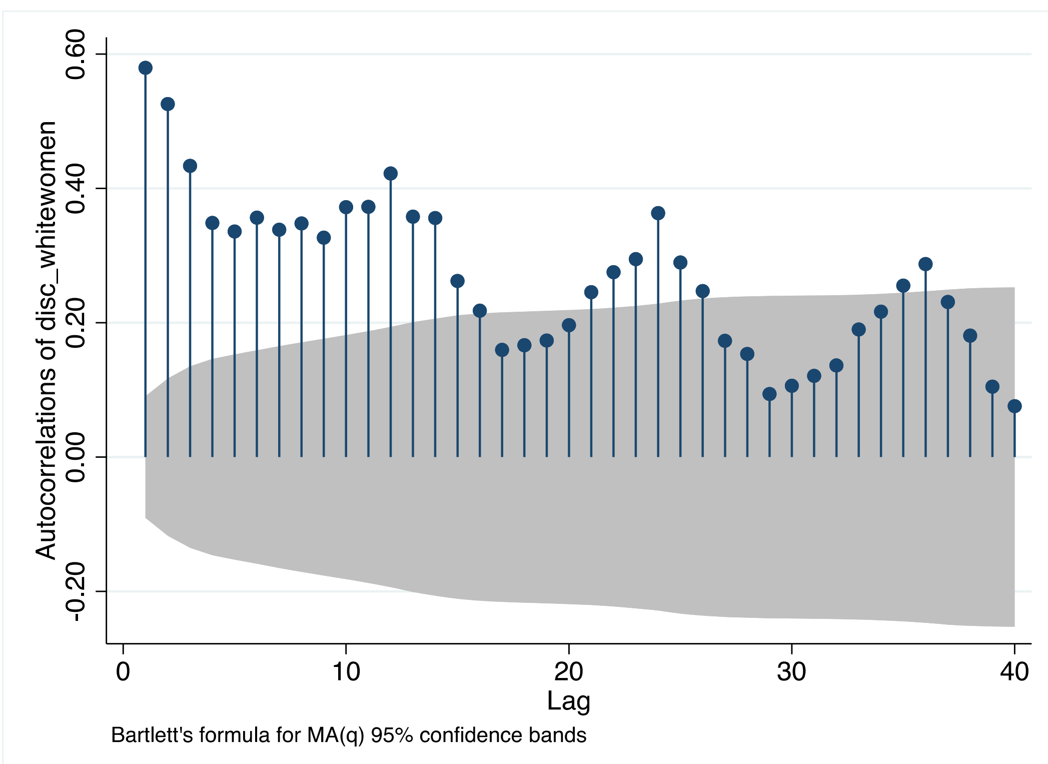

Figure A.4b Autocorrelogram for Afro-American Women

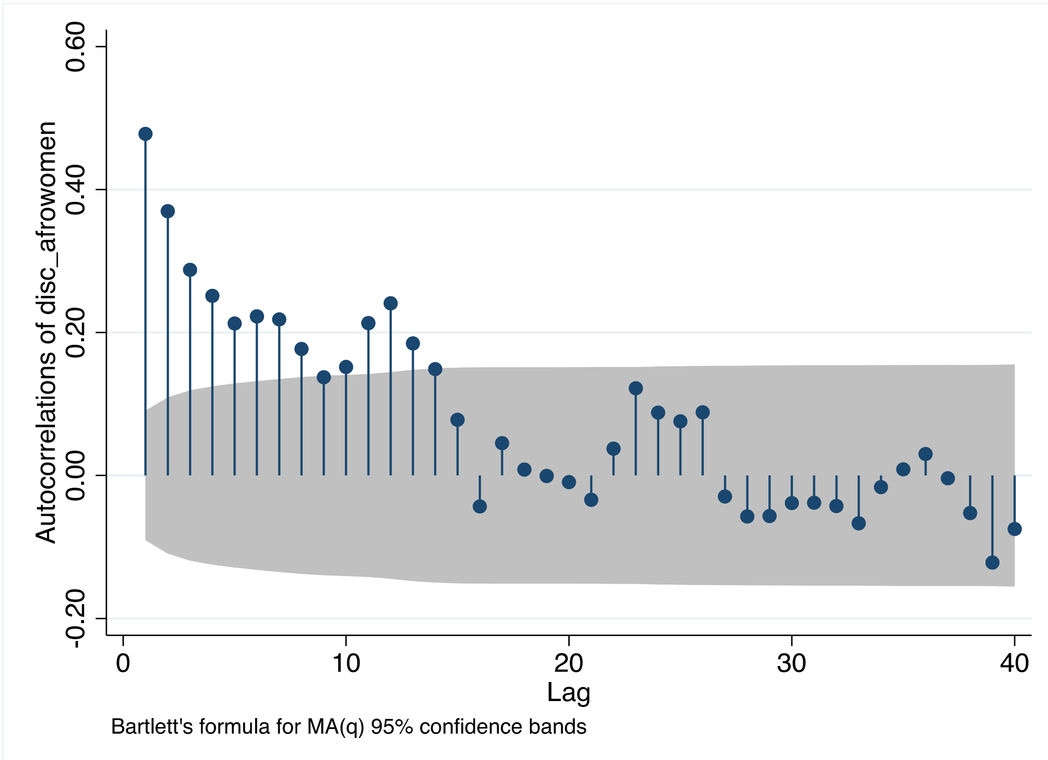

Figure A.4c autocorrelogram for Afro-American Men